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**PRICE DISCOVERY IN THE PRE-OPENING PERIOD.
THEORY AND EVIDENCE FROM THE MADRID STOCK EXCHANGE**

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Abstract

Some stock exchanges, such as the Spanish Stock Exchange and Euronext (Paris), allow traders to place orders in a 'pre-opening' period. Orders placed in this period are used to determine the opening price, and can be cancelled at any moment and at no cost by the traders. We consider a model in which noise traders can appear in the market before or after the opening, and a strategic informed trader decides her order strategy at the pre-opening and at the opening period. We characterize the equilibrium of such a model, showing that at the pre-opening there is a non-monotonic relation between the aggregate quantity ordered and prices. Thus, the equilibrium at the pre-opening stage is determined in a way which is fundamentally different from the equilibrium in the open market. We proceed to study the implications of the existence of a pre-opening period on information revelation and on the determination of the opening price. We present evidence from the Spanish Stock Exchange that seem to support the theoretical predictions, showing a clear different in behaviour between the market behaviour before and after the opening of the market.

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1 Introduction

Various stock exchanges (e.g. Madrid and Paris) have a phase of ‘price discovery’ in which agents place *tentative* orders and *tentative* prices are quoted. The orders placed in this phase are not binding, since they can be cancelled at no cost at any point before the official opening. The pre-opening phase is usually quite active and many of the orders placed turn out to be serious orders (see Biais, Hillion and Spatt (1999) for evidence from the Paris *Bourse*). It is usually thought that the pre-opening phase helps markets to ‘find the right price’ at the opening, making public the information accumulated during the no-trade period. Yet, from the theoretical point of view it is not clear why this should be the case. In particular, since orders placed in the pre-opening phase are non-binding, the first question one has to answer is: Why do agents bother to place orders at all? In particular, it appears that informed agents should be reluctant to place any order that could reveal their information.

One way to overcome the difficulty is to assume that an order placed during the pre-opening period has a strictly positive probability, although possibly very low, of being executed. This may occur either because the opening time of the market is stochastic, so that there is always a positive probability that an order will be the final one, or because problems in communication may prevent the trader from cancelling the order. The approach has first been proposed by Vives (1995a, 1995b), who considers competitive models in which a continuum of traders place limit orders. Biais, Hillion and Spatt (1999) and Medrano and Vives (2001) have introduced the presence

of a strategic informed trader, who takes into account the effect of her orders on information disclosure. In this class of models, agents place orders in the pre-opening phase because there is a positive probability that the order will be the final one. Thus, in order to exploit their superior information, informed traders place meaningful orders. However, their orders will be more ‘restrained’ than in the case in which trade occurs with probability 1. The reason is that by placing orders an informed trader reveals information, and this reduces future profits if trade does not occur in the current period.

In this paper we propose a different approach, not relying on a random opening time. Our basic intuition is that in a market in which both informed and noise traders are present, the pre-opening period provides, as a minimum, a signal on the extent of noise trading.

Consider a simple two period model, in which agents place orders at the

pre-opening period and at the ‘open market’ period. Orders at the pre-opening period are essentially cheap talk, since they can be cancelled at no cost; if not cancelled, they are executed when the market opens. Orders placed when the market is open are executed immediately. Suppose now that noise traders arrive randomly at the market, and that noise traders who place an order at the pre-opening period do not cancel it. Can there be an equilibrium in which the informed trader is not active at the pre-opening period? The answer is no. If only noise traders appear at the pre-opening, then the order flow of the pre-opening provides a signal of the extent of noise trading, and this signal is taken into account when setting the price at the opening. For example, if a market maker observes a large demand at the pre-opening, then she will be inclined to believe that a large demand in the open market is mostly the result of noise, rather than the consequence of strategic behavior on the part of the noise trader. This in turn makes the price less sensitive to the order flow. But this situation cannot be an equilibrium. An informed trader who receives good news on the asset, so that she is likely to buy the asset when the market opens, will want to increase the estimate of noise trading made by the market maker. Thus, she places orders at the pre-opening. But this contradicts the original assumption that only noise trading is active at the pre-opening.

The previous argument implies that any equilibrium must see the active participation of the informed trader at the pre-opening period, even if there is no positive probability that the market will execute the orders. This in turn implies that the order flow at the pre-opening provides a signal both about the extent of noise trading and the value of the asset. It turns out however that, differently from what happens when the market is open, the relation between the order flow at the pre-opening period and the value of the asset is not monotonic. This is a consequence of the fact that at the pre-opening period the informed trader has no incentive to reveal its information. The only reason why she is in the market is to garble the message about liquidity trading, revealing as little as possible of her information. We will show that a monotonic strategy (that is, a strategy in which the informed agent places higher orders when the value of the signal is higher) cannot be part of an equilibrium, which in turn implies that the relation between the value of the asset and the order flow cannot be monotonic. To sum up, our theoretical model predicts a quite different behavior at the pre-opening phase and at the open market, and a non-monotonic relation between the value of the asset and the order flow at the pre-opening.

We test the predictions of the theoretical model using data from the

electronic continuous market used in Spain for equity trading, known by the Spanish acronym SIBE (*Sistema de Interconexión Bursatil Español*). We observe best five levels of limit order book data over a month for the 35 most actively traded stocks in the market in the pre-opening phase. For each stock we can observe at each moment the equilibrium price and quantity as well as part of the demand and supply curve. This data can be used to check whether market behavior is different before and after the pre-opening of the market. We use LOB data to calculate demand and supply elasticity. These elasticity measures should be different depending on the moment we look at demand and supply. Closer to the end of pre-opening rational insider behavior is different than in pre-opening phase. Different elasticity figures is a signal of the presence of insiders. This effect should be more pronounced during pre-opening of highly informative days.

There exist other articles that look at elasticity. In general these articles look at demand and supply schedules during IPO. The only paper related with our research is Kalay, Sade and Wohl (2003). They compare elasticity of pre-opening vs opening period. They document that demand schedule is more elastic than supply schedule. But our research differ from Kalay, Sade and Wohl (2003) in some important points. On one hand, they study the elasticity in two completely different periods while we are interested in the evolution and behavior of elasticity. As a consequence our study is closer in spirit to Biais, Hillion and Spatt (1999) than to Kalay, Sade and Wohl (2003). On the other, given this comparison idea, we do not scale our elasticity measures by shares outstanding or volume.

We also have closing prices for stocks, that we can use to proxy for the value of the asset and check for the relation between asset value and prices and volume at the pre-opening phase. Results seem to support the theoretical predictions, showing a clear difference in market behavior depending on the timing of pre-opening.

2 The Model

There is a risky asset which can take a finite number of values:

$$V = \{v_1, \dots, v_K\}$$

with $v_i < v_{i+1}$ for $i = 1, \dots, K - 1$. The prior probability distribution of the value of the asset is given by $\mu = \{\mu_1, \dots, \mu_K\}$, with μ_i being the probability that the asset will take value v_i and $\mu_i > 0$ each i .

We will assume that trading activity takes place over two periods, structured as follows:

Pre-opening period During this period agents place market orders. The total orders are collected by a market maker, and the net amount is made public. No trading takes place at this point. We will use the subscript T (temporary) to refer to the pre-opening period.¹

Opening period During this period agents again place market orders. Orders placed at the pre-opening period are considered valid orders, unless explicitly cancelled. A market maker observes the total order flow and determines the price, setting it equal to the expected value of the asset. Orders are executed, and each agent pays (receives) the price multiplied by the order placed. We will use the subscript F (final) to refer to the opening period.

There are two types of traders in the market. The first is an informed speculator. This speculator observes the value of the asset before the pre-opening period. We denote by x_T the order placed by the informed trader at the pre-opening period, and by x_F the order placed at the opening period². We will assume that orders have to belong to a finite set $X = \{x_1, \dots, x_n\}$, where each x_i is an integer number. This is equivalent to assume that orders have to be multiple of a given minimum quantity, and there is a bound on the total amount that can be ordered. We also assume $0 \in X$ and $x_1 < 0 < x_n$. We denote by Δ^n the n -dimensional simplex, that is the space of all probability distribution on X .

Beside the informed trader we have noise traders, who can place their orders both at the pre-opening and at the opening period. The number of noise traders is random, and each noise trader places an order of size 1 or -1 . The total amount ordered by noise traders at the pre-opening period can be represented as a random variable \tilde{u}_T , with support on the set of integers

¹From the theoretical point of view, Back and Baruch (2003) show that under some assumptions the equilibria of the Glosten-Milgrom model converge to the equilibrium of the Kyle model. So we are able to use LOB data to test the model.

²For the sake of simplicity we assume that the informed trader cancels the order placed at the pre-opening period and places a new order. Therefore, when the market is open the contribution of the informed trader is simply x_F . Equivalently, we could assume that the pre-opening order is confirmed and the agent modifies it with an additional order Δx_F . In this case the contribution to the order flow in the open market is $x_T + \Delta x_F$. The first formulation saves notation.

$Z = \{\dots, -1, 0, 1, \dots\}$ and probability distribution $q = \{\dots, q_{-1}, q_0, q_1, \dots\}$, with $q_i > 0$ for each $i \in Z$ and $\sum_{-\infty}^{+\infty} q_i = 1$.

Similarly, the order placed by noise traders at the opening is represented by a random variable \tilde{u}_F , with support on Z and probability distribution $w = \{\dots, w_{-1}, w_0, w_1, \dots\}$, with $w_i > 0$ for each $i \in Z$ and $\sum_{-\infty}^{+\infty} w_i = 1$. We will assume that noise traders who place an order at the pre-opening period always confirm the order at the opening period³. The total noise order placed at the opening period is therefore $\tilde{u}_T + \tilde{u}_F$. We will denote by $z_T = x_T + \tilde{u}_T$ the order flow observed at the pre-opening period and by $z_F = x_F + \tilde{u}_T + \tilde{u}_F$ the order flow observed at the opening period.

Notice that the variable z_T is publicly observed before the beginning of the opening period, and the set of all possible orders observable at the pre-opening period and at the opening period is the set of integers Z .

A rational expectation equilibrium of this game is given by:

- a price function $p : Z \times Z \rightarrow [v_1, v_K]$, where $p(z_T, z_F)$ is the price set when the order flow z_T is observed at the pre-opening period and the order flow z_F is observed at the opening period;
- a function $\xi : Z \times Z \times V \rightarrow \Delta^n$, where $\xi(u_T, z_T, v_i)$ denotes the probability distribution on X adopted by the informed trader who has observed v_i , an order z_T at the pre-opening and a noise order u_T at the pre-opening period⁴;
- a function $\delta : V \rightarrow \Delta^n$, where $\delta(v_i)$ denotes the probability distribution on X adopted by the informed trader upon observing v_i ;

satisfying the following properties:

- The price function $p(z_T, z_F)$ is given by:

$$p(z_T, z_F) = E[\tilde{v} | x_T + \tilde{u}_T = z_T, x_F + \tilde{u}_T + \tilde{u}_F = z_F]$$

that is $p(z_T, z_F)$ is the conditional expected value of the asset given the observed order flows, where the expectation is taken making use of the probability distributions δ and ξ ;

³This assumption is not essential. All we need is that there is a noise component in the pre-opening period, and that this noise is not independent of noise trading at the opening period.

⁴The informed trader observe the pre-opening order flow z_T and knows the part of the flow due to its own order x_T . She can therefore compute the demand coming from noise traders as $u_T = z_T - x_T$.

- for each triplet (u_T, z_T, v_i) the probability distribution $\xi(u_T, z_T, v_i) = (\xi_1, \dots, \xi_n)$ is such that $\xi_i > 0$ only if:

$$x_i \in \arg \max_{x_F \in X} E[(v_i - p(z_T, x_F + u_T + \tilde{u}_F)) x_F]$$

that is an order is placed with positive probability only if it maximizes the expected profit of the informed trader, where the expectation is conditional on the informed trader's information (u_T, z_T, v_i) ;

- for each v_i , the probability distribution $\delta(v_i) = (\delta_1, \dots, \delta_n)$ is such that $\delta_i > 0$ only if:

$$x_T \in \arg \max_{x_T \in X} E[(v_i - p(x_T + \tilde{u}_T, x_F(\tilde{u}_T, x_T + \tilde{u}_T, v_i) + \tilde{u}_T + \tilde{u}_F)) x_F(\tilde{u}_T, x_T + \tilde{u}_T, v_i)]$$

where $x_F(x_T + \tilde{u}_T, \tilde{u}_T, v_i) \in \text{supp} \xi(u_T, x_T + u_T, v_i)$ for each triplet $(u_T, x_T + u_T, v_i)$, that is an order x_i is placed with positive probability only if it maximizes the expected profit, taking into account the optimal policy of the informed trader at the opening period and conditioning on the known value v_i .

We first show that a rational expectation equilibrium exists. The strategy of the informed trader can be described as follows:

- The strategy at the pre-opening period is a collection $(\delta(v_1), \dots, \delta(v_K))$, where for each v_i , we have $\delta(v_i) \in \Delta^n$. It can therefore be described as an element of the set $\Delta^{n \times K}$. We will adopt the notation $\Gamma = \Delta^{n \times K}$, and we let γ denote a generic element of Γ .
- The strategy at the opening can be described as a collection

$$\{\xi(u_T, z_T, v_i)\}_{(u_T, z_T) \in Z \times Z, v_i \in V}$$

where for each triplet (u_T, z_T, v_i) we have $\xi(u_T, z_T, v_i) \in \Delta^n$. Call Φ the set of all possible collections, that is each element $\phi \in \Phi$ is a (countable) list of probability distributions over X , one for each possible triplet $(u_T, z_T, v_i) \in Z \times Z \times V$. The set Φ represents the set of all possible strategies at the opening period. It is a convex and compact set⁵.

⁵See e.g. Royden (1988), chapter 7, exercise 30.

Let $\Omega = \Gamma \times \Phi$ the strategy space of the informed trader, a compact and convex set. Define next the space P of all possible price functions, that is P is the set of all sequences $\{p(z_T, z_F)\}_{(z_T, z_F) \in Z \times Z}$ such that $p(z_T, z_F) \in [v_1, v_K]$ for each pair (z_T, z_F) , and again observe that this is a compact and convex set.

Define now the correspondence:

$$p : \Omega \rightarrow P$$

as:

$$p^\omega(z_T, z_F) = E^\omega[\tilde{v} | \tilde{x}_T + \tilde{u}_T = z_T, \tilde{x}_F + \tilde{u}_T + \tilde{u}_F = z_F]$$

that is, for each element $\omega = (\gamma, \phi)$ the function p selects, for each pair (z_T, z_F) the expected value of v given that the informed agent uses the strategy described by γ at the pre-opening period and the strategy described by ϕ at the opening period. Notice that since both \tilde{u}_T and \tilde{u}_F have support on Z and the set X of orders by the informed trader is finite, every pair (z_T, z_F) has positive probability under any strategy ω , so that the conditional expectation is always well defined.

Given a price function p , the expected profit for the informed trader who has observed (u_T, z_T, v_i) and chosen x_F is given by:

$$\Pi(x_F, p | (u_T, z_T, v_i)) = \sum_{j \in Z} w_j (v_i - p(z_T, u_T + j + x_F)) x_F$$

where $w_j = \Pr(u_F = j)$. Let $\xi \in \Delta^n$ be a probability distribution over X , with $\xi(x_F)$ denoting the probability of choosing x_F . Define:

$$\Pi(\xi, p | (u_T, z_T, v_i)) = \sum_{x_F \in X_F} \xi(x_F) \Pi(x_F, p | (u_T, z_T, v_i)).$$

Let $\phi = \{\xi(u_T, z_T, v_i)\}_{(u_T, z_T) \in Z \times Z, v_i \in V} \in \Phi$ represent a policy followed by the informed trader at the opening period. For a given policy ϕ we set

$$\Pi(\phi, p | (u_T, z_T, v_i)) = \Pi(\xi(u_T, z_T, v_i), p | (u_T, z_T, v_i))$$

Next, define the function $\Pi^*(x_T, \phi, p | v_i)$ as:

$$\Pi^*(x_T, \phi, p | v_i) = \sum_{j \in Z} q_j \Pi(\phi, p | (j, x_T + j, v_i))$$

where $q_j = \Pr(u_T = j)$. For a probability distribution $\delta = (\delta_1, \dots, \delta_n)$ over X we define:

$$\Pi^*(\delta, \phi, p | v_i) = \sum_{k=1}^n \delta_k \Pi(x_k, \phi, p | v_i)$$

where δ_k is the probability of choosing x_k . Define the collection $\gamma = (\delta^{v_1}, \dots, \delta^{v_K})$, where δ^{v_i} denotes the probability distribution over X chosen at the pre-opening when the observed value of the asset is v_i . We define:

$$\Pi(\gamma, \phi, p) = \sum_{i=1}^K \Pr(v_i) \Pi(\delta^{v_i}, \phi, p | v_i)$$

and setting $\omega = (\gamma, \phi)$ we are going to use the more compact notation $\Pi(\omega, p)$. We now define the correspondence:

$$\theta : P \rightarrow \Omega$$

as:

$$\theta(p) = \arg \max_{\omega \in \Omega} \Pi(\omega, p)$$

For each price function p the correspondence θ selects the set of profit-maximizing trading strategies for the informed trader.

We can now prove the existence of a rational expectations equilibrium.

Proposition 1 *A rational expectation equilibrium exists.*

Proof. Since $\Pi(p, \omega)$ is continuous in (p, ω) , the theorem of the maximum ensures that the correspondence θ is u.h.c. and compact-valued. Linearity in ω ensures that the correspondence is convex-valued. Similarly, the mapping p is continuous, convex and compact valued. Therefore, by Kakutani's theorem, the mapping:

$$\theta \times p : \Omega \times P \rightarrow \Omega \times P$$

has a fixed point. Given the definitions of θ and p , the fixed point is a rational expectations equilibrium. ■

2.1 Characterization of the equilibrium

Once the existence of the equilibrium has been established, we can proceed to characterize its properties. We remind the reader that a function $f(x; t)$ satisfies *increasing differences* if whenever $t' > t$, the difference $f(x; t') - f(x; t)$ increases in x . Consider now the function $\Pi(\xi, p | (u_T, z_T, v_i))$. For a given price function p and observation (u_T, z_T) this can be seen as a function of ξ and v_i . The variable ξ belongs to Δ^n , the space of probability distributions over X . We order Δ^n using the criterion of first order stochastic

dominance (FOSD), that is $\xi \succeq \xi'$ if $\sum_{i=1}^r \xi(x_i) \leq \sum_{i=1}^r \xi'(x_i)$ for each $r \leq n$. We have the following result about the strategy of the informed trader at the opening.

Lemma 1 *For a given price function p and observation (u_T, z_T) let ξ^{v_i} be an optimal strategy chosen when the observed value of the asset is v_i . Then the strategy of the informed trader at the opening is increasing in v_i in the sense of first order stochastic dominance.*

Proof. Take as given p and (u_T, z_T) , and define $f(\xi, v_i) = \Pi(\xi, p | (u_T, z_T, v_i))$. The objective function of the informed trader is given by:

$$f(\xi, v_i) = \sum_{j=1}^n \xi_j [v_i - E(p(z_T, u_T + \tilde{u}_F + x_j))] x_j$$

where the expectation is taken over \tilde{u}_F . Therefore, if we take $v_k > v_i$ we have:

$$f(\xi, v_k) - f(\xi, v_i) = (v_k - v_i) \sum_{j=1}^n \xi_j x_j$$

Since $v_k - v_i > 0$, this difference is increasing in ξ . Since the objective function satisfies increasing differences, the optimal action $\xi(v_i)$ is non-decreasing in v_i . ■

We can use lemma 1 to provide a first characterization of the price function.

Lemma 2 *In each rational expectations equilibrium the price function $p(z_T, z_F)$ is non-decreasing in z_F for each given z_T .*

Proof. For each given \tilde{u}_T , lemma 1 implies $E[v | z_T, z'_F, \tilde{u}_T] \geq E[v | z_T, z_F, \tilde{u}_T]$ whenever $z'_F > z_F$. This in turn implies:

$$p(z_T, z'_F) = E^{\tilde{u}_T} [E[v | z_T, z'_F, \tilde{u}_T]] \geq E^{\tilde{u}_T} [E[v | z_T, z_F, \tilde{u}_T]] = p(z_T, z_F)$$

■

The properties of the price function described in lemma 2 are standard. The informed trader wants to increase the size of its order when she obtains better information, so that the market maker interprets an increase in the order flow as a noisy signal of the value of the assets. This leads to a function p increasing in z_F .

The more interesting part however is the characterization of the equilibrium at the pre-opening stage. We start observing that in general at the pre-opening stage the informed trading *must* be active, meaning that she chooses different strategies in dependence of different observed values of the asset.

Lemma 3 *There is no equilibrium in which the informed agent follows a constant policy at the pre-opening period.*

Proof. Suppose first that the informed agent always selects the same quantity x^* for each value v_i , and assume that $x^* > x_1$, where x_1 is the lowest possible order. This implies that for every order flow z_T at the pre-opening period the market maker is able to infer exactly the amount of noise trading as $u_T = z_T - x^*$.

Consider now the informed agent who has observed v_1 , the lowest possible value of the asset. This trader will only post negative orders at the opening period, since $p(z_T, z_F) \geq v_1$ for each realization (z_T, z_F) . This implies that in this case the informed agent wants to obtain a price at the opening which is as high as possible. This in turn implies that she wants to convince the market maker that the demand at the opening comes mostly from the informed trader, and liquidity demand is low. Finally, this implies that upon observing v_1 the informed agent can profitably deviate from x^* to x_1 , the lowest possible order.

If $x^* = x_1$ then we can apply a similar argument to show that the informed trader has a profitable deviation when the highest possible value v_K for the asset is observed.

The argument can be directly extended to mixed strategies. If the same mixed strategy is being used by the informed trader for each v_i then the order flow z_T is considered by the market maker as a noisy signal of u_T , with no information about the value of the asset. Then the informed agent who has observed v_1 can profitably deviate to x_1 , while the informed agent who has observed v_K can profitably deviate to x_n . ■

The lemma implies that in every equilibrium there is non-trivial action at the pre-opening stage by the informed trader. By this we mean that the informed trader intervenes at the pre-opening stage selecting different strategies depending on the information possessed.

The next observation is that in a rational expectations equilibrium the informed trader does *not* select a monotonic strategy at the pre-opening period.

Lemma 4 *There is no equilibrium in which the informed agent adopts a monotonically increasing policy at the pre-opening period.*

Proof. (Sketch) Suppose that the informed agent selects a monotonically increasing strategy, so that δ^{v_i} dominates δ^{v_j} in the sense of first order stochastic dominance whenever $v_i > v_j$. We first observe that in this case, given two order flows $z'_T > z_T$, the conditional probability distribution of v given z'_T first-order stochastically dominates the conditional probability distribution of v given z_T . This follows from the fact that z_T is a noisy signal of x_T , which in turn is a noisy signal of v .

Next we observe that the informed trader who has observed v_K , the highest possible value, prefers that the conditional distribution of the market maker be as low as possible in a FOSD sense, while the informed trader who has observed v_1 has preferences which are exactly the opposite. The reason is that the only way in which it can be worse for type v_K that the market maker has a lower estimate of v is that in this case the market maker forecasts a more aggressive bidding by the informed trader, so that the price function is more sensitive to z_F . This would prevent the informed trader from placing larger orders at the opening. But a more aggressive belief cannot be self-confirming, because in this case the informed trader would be less aggressive.

This implies that type v_K will want to deviate and adopt at the pre-opening stage a strategy adopted by lower types, in order to induce a lower price at the opening. An analogous deviation is available for type v_1 ■

What are the empirical predictions of the model presented in this section? The existence of the pre-opening period provides information which is valuable for the determination of the price at the opening, since it provides a signal on the extent of liquidity demand. The informed trader tries to manipulate this signal, taking advantage of the fact that the orders placed in this phase are basically ‘cheap talk’ and can be cancelled at no cost.

In temporary equilibrium the relation between the total order flow and the

extent of liquidity trading cannot be monotonic. If this were the case, an informed trader who has a high probability of being on the buying side at the opening (which happens when a high value of v is observed) would place a high order, so to convince the market maker that most of the demand comes from liquidity traders. However, in a final rational expectation equilibrium this maneuvering cannot occur, since the market maker would consider a high level of demand at the pre-opening as a signal of a high value of the

asset.

If a price is computed at the pre-opening stage, and the price is set equal to expected value of the asset, then the pre-opening price will not have a monotonic relation with the asset's value. The monotonic relation is restored when the market opens, since in this case orders are executed and the only way in which an informed trader can take advantage of her information is by following an order strategy monotonically related to the asset value.

We will use LOB data in order to compare different moments of pre-opening period. Given that we can not detect insider presence and data do not provide identification code of investors, we will use elasticity measures as a proxy of aggregated investor behavior and asymmetric information. Changes in supply and demand elasticity figures along pre-opening period will be a signa of changes in investors behavior.

3 Empirical Analysis

In this section we provide a description of the institutional features of the Spanish stock market and of the data we plan to use for the empirical analysis.

3.1 Institutional Organization of the Spanish Stock Market

The market for equities in Spain (SIBE) is organized as an electronic continuous market. It is a nationally unified market, in which a single order book exists for each stock. During the period object of the analysis (November 1999) a day of trade was divided into three parts:

1. *pre-opening period*, from 9:00 am to 10:00 am. In this period modifications, cancellations and introduction of limit orders are allowed. Depending on demand and supply on every stock the system calculates in real time a pre-opening price; when there are multiple equilibrium prices, the one that maximizes the volume traded is chosen.

At 10:00 am the system determines the opening price. Orders entered previously and not cancelled are now executed. Priority is first by price and then by time of introduction.

2. *Open Market period*, from 10:00 am to 17:00 pm. In this period limit and market orders are introduced and if a counterpart is found they are automatically executed. If not, the order remains in the book until

an incoming order fits it, or the order is cancelled. In this period prices of the stocks are changing in real time depending on the flow of buy and sell orders.

3. *Special Operations period*, from 17:30 pm to 20:00 pm. During this period pre-agreed block trades are reported.

The market is still organized in this way, but now the pre-opening period runs from 8:30 am to 9:00 am and the open market period runs from 9:00 am to 17:30 pm.

The open market is an order driven market. De Jong, Nijman and Röell (1996), among others, point out that trading mechanism operating in markets driven by orders can be formally described by the ideal electronic open limit order book framework proposed by Glosten (1994). Glosten (1994) theoretical model show how information flow cause price revisions by trading throughout the limit order book mechanism. Glosten develops both average and marginal price functions from the point of view of the agent providing liquidity. These functions are supply and demand functions. From the empirical point of view Martinez, Rubio and Tapia (2000) and Blanco (1999) discusses similar functions, and construct supply and demand functions. These analysis are developed in an open market situation but give us insights about the information that should be present in supply and demand functions.

The pre-opening period is similar to the open market trading mechanism, with the important difference that during the pre-opening period there is no transaction and orders are left unmatched. However, during the pre-opening period the Exchange uses the order to determine in real time the equilibrium price and the quantity traded at that price. So, whenever an order is cancelled, modified or a new order arrives the equilibrium price and quantity are changed. The opening price is set at 10:00, and the transactions are actually carried on. BHS describes the pre-opening process of Paris Bourse, SIBE pre-opening is quite similar to Paris procedure.

3.2 Data and Methodology

The open limit order book contains information about the five best prices on the selling and buying side for all assets.

Insert Table 1

Table 1 shows best five levels of one asset at two successive moments right before the opening of the market and right after the opening of the market on November 1, 1999. The book (including prices, volume of shares outstanding at that price and number of orders which supports such volume) was observable by market participants at every moment during the pre-opening and the open market period. Investors were also able to observe the equilibrium price. Furthermore, whenever a new order is entered the limit order book shows the new values of the variables, while the time stamp indicates exactly the time of this change (approximated by tenths of a second).

In November 1999 the continuous system of SIBE included approximately 132 assets. We analyze the behavior of the 35 most actively traded stocks.⁶ Our sample period covers all trading days of November 1999. For each trading day we consider the time period between 9:30 am and 10:00 am, comprising the last half hour of the pre-opening period.

The predictions of the model spelled out in section 2 are that insiders behaviour is different in the pre-opening than in open market period. As a consequence this behaviour should be also different between two any moment and the end of the pre-opening. One variable that should reflect this different behaviour is demand and supply schedules. Closer to the equilibrium insiders should be present at the end but not in any other moment of the pre-opening. This evidence will be a signal of structurally different behavior for the supply and demand functions along pre-opening period. These differences should be especially important for stocks exhibiting a high degree of asymmetric information.

The empirical analysis is intended to answer two questions.

1. Are the supply and demand functions observed at the pre-opening period different at the end of pre-opening period?
2. Which variables like, volatility or activity variables affect this behavior?

In order to answer these questions and test empirical implications of the model, we use the Limit Order Book (LOB) and we calculate two slopes for demand and two slopes for supply. As we mentioned, we consider time period between 9:30 am and 10:00 am (pre-opening period).

⁶Activity is measured by mean effective volume six months before the sample period.

3.3 Slopes in the pre-opening Period

During the pre-opening period, additionally to demand and supply LOB provides equilibrium price and quantities. The market calculates these equilibrium variables. Suppose that you observe the complete LOB at a given moment, and the equilibrium price P^* and volume Q^* at the same moment.

Table 2 here

With this LOB we can build a complete demand and supply functions.

Insert Figure 1

If we only observe best five levels of LOB instead of complete LOB.

Bid		Ask	
Q_{bid1}	P_{bid1}	Q_{ask1}	P_{ask1}
Q_{bid2}	P_{bid2}	Q_{ask2}	P_{ask2}
Q_{bid3}	P_{bid3}	Q_{ask3}	P_{ask3}
Q_{bid4}	P_{bid4}	Q_{ask4}	P_{ask4}
Q_{bid5}	P_{bid5}	Q_{ask5}	P_{ask5}

Slopes A and B are given by:

$$\text{If } P^* > P_{kj} \quad \rightarrow \quad \begin{aligned} A_k &= \frac{P^* - P_{k1}}{Q^* - Q_{k1}} \\ B_k &= \frac{P^* - P_{k5}}{Q^* - \sum_{j=1}^5 Q_{kj}} \end{aligned} \quad \forall j > 1$$

where k represent ask or bid prices and j represent level of prices of the limit order book. See an example: suppose that you observe the LOB of Table 1, an equilibrium price of $P^* = 15.65$, and an equilibrium quantity of $Q^* = 35634$.

Bid		Ask	
14094	17.99	13.31	19235
77	17.90	14.00	2260
700	17.50	15.00	1120
12695	17.00	15.40	3000
5000	16.75	15.44	350

Then bid side slopes are given by:

$$A_{bid} = \frac{P^* - P_{bid1}}{Q^* - Q_{bid1}} = \frac{15.65 - 17.99}{35634 - 14094} = -0.01086351$$

$$B_{bid} = \frac{P^* - P_{bid5}}{Q^* - \sum_{j=1}^5 Q_{bidj}} = \frac{15.65 - 16.75}{35634 - 32566} = -0.03585398$$

And ask side slopes by:

$$A_{ask} = \frac{P^* - P_{ask1}}{Q^* - Q_{ask1}} = \frac{15.65 - 13.31}{35634 - 19235} = 0.01426916$$

$$B_{ask} = \frac{P^* - P_{ask5}}{Q^* - \sum_{j=1}^5 Q_{askj}} = \frac{15.65 - 15.44}{35634 - 25965} = 0.00217189$$

These slopes give us information about sensitivities of demand and supply and information asymmetries. Not surprisingly, in order to calculate A and B slopes, we need two demand (supply) prices higher (lower) than the equilibrium price.

4 Results

We calculate slopes in the pre-opening when it is possible, that is when there is an equilibrium and we observe at least two prices in order to be able to compute the slopes. We are interested in the question of whether the A slopes are different from the B slopes, so that we calculate one additional measure: $Log(\frac{A}{B})$

This measure will capture differences between slopes. When $Log(\frac{A}{B})$ is greater (lower) than 0 A is greater (lower) than B. this variable will permit

to observe changes in both slopes. Given degree of transparency, it could be the case that observed quotes are not closest prices from equilibrium price (like the example). In order to match theory, and avoid this problem, we select from the whole sample observations where equilibrium price is between best first and fifth level of LOB. Additionally, we eliminate extreme observations of our sample. So, results are derived from the restricted sample without extreme values. An observation is considered an extreme one if it exceeds three times standard deviation.

In order to separate different effects, we will use two different variables. First is time to pre-opening to end. To capture seasonality effects we divide our sample in three different periods, one for each ten minutes interval. It is well known the last minutes of the pre-opening period tend to be more active (see Biais et al (1999) for evidence on Paris and Sola (2000) for Madrid). Additionally, one consequence of the model is that the behavior of investors is different in pre-opening depending on the time before the end. Both effects should be present in the level and changes of slopes.

Second effect is cross section effect. Although, we only consider 35 assets, Spanish stock exchange is a concentrated market. Over 132 firms, selected 35 firms represent more that 90% of effective volume of the whole sample. Additionally, we divide our 35 sample into 5 activity groups. Next table show group effective volume a month before the study. We can observe that subsamples are so different.

Insert Table 3-I

Table 3-II median of values the sample

Insert Table 3 and Figure 2

Looking at classification by activity group, we observe that groups 4 and 3 have higher values of slopes bothn on Ask and Bid. One result is that $Log(\frac{A}{B})$, it is interesting to observe that slopes A and B of largest companies are more equal than the other companies.

We find greater number of observations as the end of pre-opening period comes closer. In general, looking at $Log(\frac{A}{B})$ results it seems that ask and bid side differ in their behavior. On one hand, Ask side show a median rising value at least if we compare first ten minutes with the rest of the sample. This results implies that A slope on the ask side becomes greater (between 2 and 3 times) than B or B is more elastic. This implies that prices close to equilibrium are more liquid. On the other hand, Bid side median $Log(\frac{A}{B})$ variable becomes closer to cero. As in the Ask side, A is greater than B but contrary to Ask result differences between both slopes are decreasing and both slopes are becoming more inelastic.

If we take into account the whole sample, assets with the largeest level of activity (5) are the ones with most observations. However, if we only look at restricted sample, then the group with more observations is group 5. Additionally, the number of observations is not monotonic in the capitalization.

In fact, group 3 firms have a greater number of slope observations than the any other activity classification except group 5. As expected, the number of observations computed in a given time interval during the pre-opening period increases as the time approaches the opening period.

4.1 Seasonality and Cross-sectional Effects

The first analysis we carry out is about seasonality. In order to capture seasonality effects we construct 3 dummy variables in the pre-opening period, one for ten minutes interval. We run one regression. Results are in table 3.

$$y_{it} = \alpha + \beta_2 D_2 + \beta_3 D_3 + \varepsilon_{it}$$

Insert table 4

where β_2 and β_3 refers to 20 to 10 minutes to end pre-opening and 10 to 0 minutes to end pre-opening and y_{it} refers to either slope A , B or $\text{Log}(\frac{A}{B})$ either bid or ask.

We can observe some important differences between slopes and between ask and bid side. Looking at ask results, table shows that pre-opening ending implies that market ask side becomes more elastic and as a consequence more liquid, that is equilibrium price is less sensitive to changes in order flow. This increase in liquidity is higher in A slopes so higher improvement of liquidity is far away from equilibrium price. This result implies that liquidity improvement occurs far away from the equilibrium price so there are less insider camouflage opportunities close to equilibrium price. However, this result is not confirmed by $\text{Log}(\frac{A}{B})$.

When we look at bid results A slope does not significantly change. We observe the opposite result in B slope. B slope changes are significant and negative. This implies lower liquidity around equilibrium price (absolute value of slope is rising). Given the value of $\text{Log}(\frac{A}{B})$ for the bid side, A slope is greater than bid slope close to equilibrium price but less that at the begining of the pre-opening period.

We calculate cross-sectional effects in the same way. we construct five dummy variables, one for each group considered. Given the differences among groups, we should expect different degree of asymmetric information and as a consequence different slope behavior. We run one regression for each endogeneous variable. Results are in table 5.

$$y_{it} = \alpha + \beta_4 D_4 + \beta_3 D_3 + \beta_2 D_2 + \beta_1 D_1 + \varepsilon_{it}$$

Insert table 5

where y_{it} refers to either slope A , B or $Log(\frac{A}{B})$ and to either bid or ask.

One interesting result is that, groups of lowest and highest activity show higher elasticity. So, highest and lowest levels of activity are more liquid than groups 4 and 3. Although $Log(\frac{A}{B})$ variable present similar idea, we observe that on ask side constant is not statistically different from zero. This implies that A and B slopes are not statistically different. But this result does not maintain for the rest of the groups where results are similar among them. On the other hand, Bid side present a completely different result for $Log(\frac{A}{B})$. In this case, group 5 is different from zero and the other groups are not homogeneous. The last result show a different degree of asymmetric information between both sides depending on the group we look at.

4.2 Volatility effect

The volatility of asset prices is influenced by the rate at which new information arrives and by the rate at which private information is disclosed. Since the predictions of our model depend on the presence of informed traders, it is useful to see how volatility influences the pre-opening slopes of demand and supply curves.

First, we should construct a volatility measure. Based solely on Andersen et al (2001) we construct daily volatility measure. We first define returns as:

$$r(j, t) = Log(S(j, t)) - Log(S(j - 1, t))$$

where S is the price of asset on day t between j and j-1 time interval. Second, daily volatility proxy is a mean average of absolute value of returns.

$$\sigma_S^2 = \frac{1}{N} [\sum abs(r(j, t))]$$

Third, given that we try to detect differences in asymmetric information level we calculate a ratio between each asset volatility variable by mean sample volatility of assets included in the sample.

$$R(\sigma_S^2) = \frac{\sigma_S^2}{\frac{1}{N} [\sum \sigma_S^2]}$$

In addition, we detect two most volatile days for each asset and build a dummy variable for those days. First analysis we carry out is a regression analysis with these dummy variable (D_{90}) which takes value 1 if

$R(\sigma_S^2)$ belongs to the top deciles and 0 otherwise. These observations in which $D_{90} = 1$ correspond to days and assets in which important movements occur from pre-opening to closing price, presumably because of information disclosure. We run the next regression for each side and each variable.

$$y_{it} = \alpha + \beta D_{90} + \varepsilon$$

Insert table 6

Results can be summarize indicating that arrival information days exhibit different behavior in pre-opening slopes. Slopes are greater or equal than days of lower volatility that slopes is more inelastic or the market is less liquid. This result implicates that before higher volatility days we can detect higher asymmetric information level and as a consequence more inelastic demand and supply curves. Looking at Ask slopes, A slope is more inelastic and B is not different. Contrary to this result $Log(\frac{A}{B})$ is lower on volatility days. So, volatile days are less liquid and investors are more confident about the absence of information and as a consequence the lower level of liquidity. When we observe Bid side, slopes become greater in absolute value. This change is greater in B slope. Again, $Log(\frac{A}{B})$ does not significantly change. Bid side is less liquid those volatile days.

Given the role of volatility in the analysis, we look at interactions between time dummy and volatility dummy in order to capture different behavior those volatile days. We run the next regression.

$$y_{it} = \alpha + \beta_2 D_2 + \beta_3 D_3 + \beta_{90} D_{90} + \gamma_{90}^2 (D_2 * D_{90}) + \gamma_{90}^3 (D_3 * D_{90}) + \varepsilon_{it}$$

Insert table 7

Looking at results interaction show different sign that direct effects when they are significant. This effect is specially important in $Log(\frac{A}{B})$ variable and in B Bid variable. A Ask direct coefficient. These volatile days, Ask $Log(\frac{A}{B})$ variable, exhibit higher differences in asymmetric information captured by interaction coefficients. With possitive coefficient in direct coefficient (β_{90}) and negative coefficients of indirect effects ($\gamma_{90}^2, \gamma_{90}^3$). Similar results can be found in B slope on the Bid side but not on $Log(\frac{A}{B})$ variable. Main conclusions of this table are that interactions are relevant in order to explain slopes behavior on higher volatility days and interactions coefficients are of different sign than direct coefficient.

The second analysis related with information arrival use volatility and activity variables to explain the behavior of slopes. Now instead of pre-opening observations, we summarize slopes information in two different measures. First measure is a mean of slopes values for each asset each day. Second measure is a dispersion ones. We define

$$y_{i,MaxMin} = Max(y_{it}) - Min(y_{it})$$

To carry out this analysis we will use daily observations and we run the next regression

$$\bar{y}_{it} = \alpha + \gamma_1 Log(R(\sigma_{S,t-1}^2)) + \gamma_2 Log(NMS_{it-1}) + \gamma_3 Log(Vol_{it-1}) + \varepsilon_{it}$$

where \bar{y}_{it} can be mean of slopes for each day and each asset or the dispersion measure, $y_{i,MaxMin}$. Exogeneous variables are measure the day before and they are volatility, Normal Market Size (effective volume per transaction) and Volume in shares.⁷

Insert table 8

First result of the table is that signs are consistent that is exogenous variables affect in the same way to endogenous variables. Higher volatility and shares volume the day before implies higher liquidity. Contrary effect is Normal Market Size variable. Normal Market Size decrease liquidity becoming more inelastic demand and supply schedules. Complementary analysis is given by analyzing if contemporary volatility measure with $y_{i,MaxMin}$ affect slope behavior. We run next regression.

$$\bar{y}_{it} = \alpha + \gamma_1 Log(\sigma_{it-1}) + \gamma_2 Log(NMS_{it-1}) + \gamma_3 Log(Vol_{it-1}) + \gamma_A A_{i,MaxMin} + \gamma_B B_{i,MaxMin} + \varepsilon_{it}$$

Results are included in table 9.

Insert table 9

Looking at results we observe that contemporary dispersion measures affect mean slopes. Signs and significance show that greater dispersion in slopes affect negatively to liquidity closer or not of the equilibrium. It is important to note that results are so similar when we use median instead mean slope measure. Greater dispersion that is greater range between maximum and minimum or greater differences of opinion becomes less liquid the market. This result is asymmetric for both sides and both slopes.

⁷A correlation analysis show that there is no multicolineality problems.

5 Conclusions

We can consider at least three reasons why pre-opening is an important period. Protocol procedure is different from open market period, it provides price discovery, and investors use it as an important part of the market. In SSE pre-opening can cross between 20 and 30% of daily effective volume.

Our model implies that a rational expectation equilibrium exists with the active participation of the informed trader and uninformed traders. An important theoretical result is that informed trader selects different strategies depending on the information possessed.

The empirical part is based on the study of behavior of LOB slopes. Main results indicate behavior of investors is different depending where they put the orders, close or not to the equilibrium price. Slopes show great degree of time dependency and size effect.

Additionally, some variables affect behavior of slopes and Information arrival days exhibit different behavior in pre-opening slopes.

Most important result is that contemporary dispersion measure or a measure of differences in opinion has a direct impact on slope level. Greater differences imply steeper slopes or less liquid market. Also, this result is true for both sides and both slopes.

These results are consistent with our model.

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Figure 1

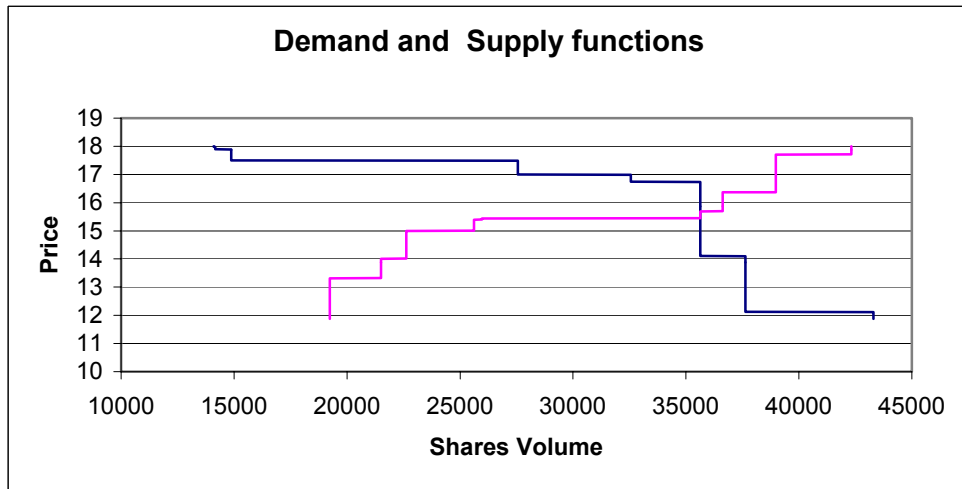


Figure 2

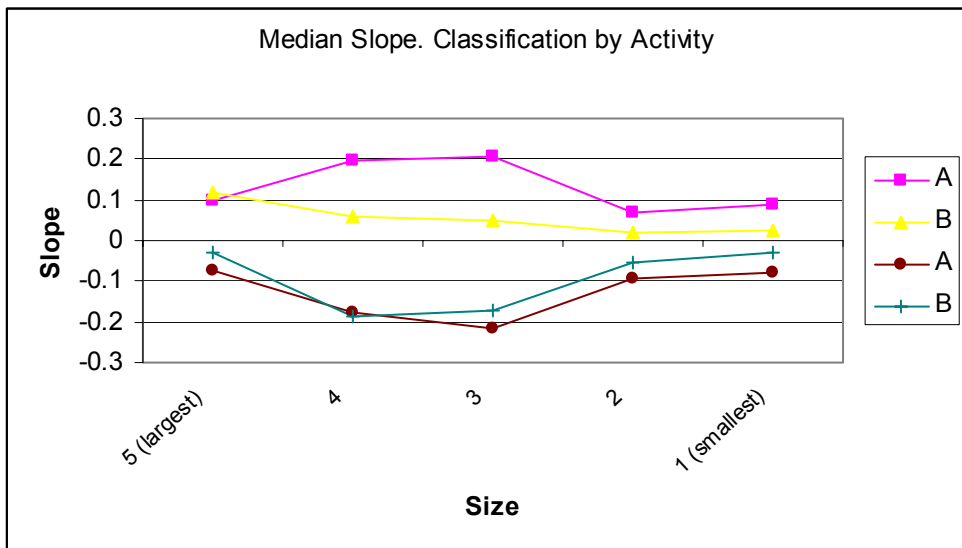


Table 1

LOB at 9:59:59

Bid		Ask	
14094	17.99	13.31	19235
77	17.90	14.00	2260
700	17.50	15.00	1120
12695	17.00	15.40	3000
5000	16.75	15.44	350

LOB at 10:00:10

Bid		Ask	
151	15.54	15.70	2534
1537	15.53	15.71	1336
835	15.50	15.72	1200
1300	15.48	15.73	504
3000	15.47	15.74	3307

Table 2

LOB at 9:59:59

Bid		Ask	
14094	17.99	13.31	19235
77	17.90	14.00	2260
700	17.50	15.00	1120
12695	17.00	15.40	3000
5000	16.75	15.44	350
3068	16.50	15.60	9669
2000	14.00	15.70	1000
5673	12.00	17.00	3345

P*=15,65

Q* =35634

Table 3-I
Descriptive Statistics

This table contains Descriptive Statistics of Size Groups looking at Effective Volume (EV)

<i>Panel A: Slope Classification by Activity</i>		
	<i>Group EV/ Total Sample EV</i>	<i>Group EV/ Market EV</i>
5 (largest)	82.1	74.8
4	10.6	9.6
3	4.0	3.8
2	2.0	1.8
1 (smallest)	1.3	1.3
Total	100.0	91.3

Table 3-II
Descriptive Statistics

This table contains Descriptive Statistics of slopes in preopening. (A_{ASK} , B_{ASK} , $\text{Log}(A/B)_{ASK}$, A_{BID} , B_{BID} , $\text{Log}(A/B)_{BID}$).

<i>Panel A: Median Slope. Classification by Activity</i>						
	<i>Ask</i>			<i>Bid</i>		
	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>
5 (largest)	0.098	0.118	0.017	-0.074	-0.030	0.575
4	0.197	0.061	0.967	-0.178	-0.185	0.083
3	0.205	0.050	1.226	-0.217	-0.174	0.222
2	0.070	0.019	1.145	-0.095	-0.052	0.553
1 (smallest)	0.088	0.024	1.021	-0.078	-0.031	0.651
All sample	0.116	0.041	0.862	-0.119	-0.070	0.504

<i>Panel B: Median Slope. Classification by Minute</i>						
	<i>Ask</i>			<i>Bid</i>		
<i>Min.</i>	<i>A</i>	<i>B</i>	<i>LOG(A/B)</i>	<i>A</i>	<i>B</i>	<i>LOG(A/B)</i>
0-9	0.141	0.061	0.675	-0.144	-0.035	0.889
10-19	0.160	0.050	0.942	-0.120	-0.067	0.447
20-29	0.084	0.034	0.859	-0.118	-0.101	0.320
All sample	0.116	0.041	0.862	-0.119	-0.070	0.504

Table 4
Dummy Time Regression

This table contains the time series coefficients of slopes in preopening. The dependent variable is one of the slope variable (A_{ASK} , B_{ASK} , $\text{Log}(A/B)_{ASK}$, A_{BID} , B_{BID} , $\text{Log}(A/B)_{BID}$). The explanatory variables are two dummy variables that capture time till the end of the preopening period effect. ***, ** and * indicates significance at 1%, 5% and 10% respectively.

$$y_j = \alpha + \beta_2 D_2 + \beta_3 D_3 + \varepsilon_j$$

	<i>Ask</i>			<i>Bid</i>		
	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>
α	0.454 ***	0.457 ***	0.868 ***	-0.370 ***	-0.395 ***	0.905 ***
β_2	-0.039	0.040	0.172 **	-0.019	-0.273 ***	-0.441 ***
β_3	-0.218 ***	-0.110 **	0.051	0.003	-0.191 ***	-0.426 ***

Table 5
Activity Effect Regression

This table contains the Activity influence on slopes in preopening. The dependent variable is one of the slope variable (A_{ASK} , B_{ASK} , $\text{Log}(A/B)_{ASK}$, A_{BID} , B_{BID} , $\text{Log}(A/B)_{BID}$). The explanatory variables are four dummy variables that capture Activity or Size effect. ***, ** and * indicates significance at 1%, 5% and 10% respectively.

$$y_j = \alpha + \beta_4 D_4 + \beta_3 D_3 + \beta_2 D_2 + \beta_1 D_1 + \varepsilon_j$$

	<i>ASK</i>			<i>BID</i>		
	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>
α	0.239 ***	0.552 ***	-0.096	-0.403 ***	-0.553 ***	0.522 ***
β_4	0.344 ***	-0.081	1.210 ***	-0.263 ***	-0.521 ***	-0.240 **
β_3	0.246 ***	0.129	1.258 ***	-0.035	-0.134 *	-0.138
β_2	-0.053 ***	-0.339 ***	1.231 ***	0.166 ***	0.289 ***	0.126
β_1	-0.010	-0.328 ***	1.205 ***	0.200 ***	0.191 **	0.335 ***

Table 6
Volatility Dummy Regression

This table contains volatility influence on slopes in preopening. The dependent variable is one of the slope variable (A_{ASK} , B_{ASK} , $\text{Log}(A/B)_{ASK}$, A_{BID} , B_{BID} , $\text{Log}(A/B)_{BID}$). The explanatory variable is a Dummy variable that reflect higher volatility day. ***, ** and * indicates significance at 1%, 5% and 10% respectively.

$$y_j = \alpha + \beta_{90} D_{90} + \varepsilon_j$$

	<i>Ask</i>			<i>Bid</i>		
	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>	<i>A</i>	<i>B</i>	<i>Log(A/B)</i>
α	0.349 ***	0.429 ***	0.969 ***	-0.367 ***	-0.557 ***	0.560 *
β_{90}	0.062 **	-0.009	-0.212 **	-0.068 *	-0.177 **	0.018

Table 7
Time of Pre-opening and Volatility Dummy Regression

This table contains Time of Preopening, Activity and Volatility influence on slopes in preopening including interaction effects. The dependent variable is one of the slope variable (A_{ASK} , B_{ASK} , $\text{Log}(A/B)_{ASK}$, A_{BID} , B_{BID} , $\text{Log}(A/B)_{BID}$). The explanatory variables are Dummy variables that reflect Time of Preopening, Activity and higher volatility day and interaction among them. ***, ** and * indicates significance at 1%, 5% and 10% respectively.

$$y_j = \alpha + \beta_2 D_2 + \beta_3 D_3 + \beta_{90} D_{90} + \gamma_{90}^2 (D_3 * D_{90}) + \gamma_{90}^3 (D_3 * D_{90}) + \varepsilon_j$$

	<i>Ask</i>						<i>Bid</i>					
	<i>A</i>		<i>B</i>		<i>Log(A/B)</i>		<i>A</i>		<i>B</i>		<i>Log(A/B)</i>	
α	0.458	***	0.435	***	0.949	***	-0.358	***	-0.418	***	0.892	***
β_2	-0.051		0.077		0.098		-0.024		-0.208	***	-0.436	***
β_3	-0.231	***	-0.088		-0.039		-0.003		-0.145	***	-0.401	***
β_{90}	-0.048		0.209		-0.804	***	-0.089		0.164	**	0.092	
γ_{90}^2	0.139	*	-0.400	***	0.726	*	0.037		-0.492	***	-0.033	
γ_{90}^3	0.145	**	-0.217		0.920	***	0.019		-0.413	***	-0.219	

Table 8
Volatility Regression.

This table contains volatility and activity variables influence on slopes and dispersion measures in preopening. The dependent variable is one of the slope or dispersion variable (A_{ASK} , B_{ASK} , $\text{Log}(A/B)_{ASK}$, A_{BID} , B_{BID} , $\text{Log}(A/B)_{BID}$) as an average of each variable or the dispersion ones ($A_{ASK, \text{MaxMin}}$, $B_{ASK, \text{MaxMin}}$, $\text{Log}(A/B)_{ASK, \text{MaxMin}}$, $A_{BID, \text{MaxMin}}$, $B_{BID, \text{MaxMin}}$, $\text{Log}(A/B)_{BID, \text{MaxMin}}$). The explanatory variables are volatility measure as Andersen et al (2001), natural logarithm of Mean Effective Normal Market Size for each asset and natural logarithm of Mean Volume in shares. All variables are measured the day before for each asset in the sample. ***, ** and * indicates significance at 1%, 5% and 10% respectively.

$$\bar{y}_{it} = \alpha + \gamma_1 R(\sigma_{St-1}^2) + \gamma_2 \text{Log}(NMS_{it-1}) + \gamma_3 \text{Log}(Vol_{jt-1}) + \varepsilon_j$$

	<i>Ask</i>						<i>Bid</i>					
	<i>A</i>		<i>B</i>		<i>Log(A/B)</i>		<i>A</i>		<i>B</i>		<i>Log(A/B)</i>	
α	1.503	***	1.391	**	1.622	**	-0.396	**	-1.455	***	-0.872	
γ_1	-0.105	***	-0.098		-0.196		0.040		0.162	**	0.342	*
γ_2	0.397	***	0.178		1.207	***	-0.663	***	-0.677	***	0.348	
γ_3	-0.236	***	-0.161	**	-0.334	***	0.153	***	0.277	***	0.111	

Table 9
Volatility Regression.

This table contains volatility activity and dispersion measures influence on slopes in preopening dispersion of each of the variables considered in the analysis. The dependent variable is one of the slope variable (A_{ASK} , B_{ASK} , $\text{Log}(A/B)_{ASK}$, A_{BID} , B_{BID} , $\text{Log}(A/B)_{BID}$) as an average of each variable each day. The explanatory variables are volatility measure as Andersen et al (2001), natural logarithm of Mean Effective Normal Market Size for each asset and natural logarithm of Mean Volume in shares. All variables are measured the day before for each asset in the sample. Dispersion measures are defined as maximum minus minimum of the slopes estimated for each day and each asset. ***, ** and * indicates significance at 1%, 5% and 10% respectively.

$$\bar{y}_{it} = \alpha + \gamma_1 R(\sigma_{it-1}^2) + \gamma_2 \text{Log}(NMS_{it-1}) + \gamma_3 \text{Log}(Vol_{jt-1}) + \gamma_A A_{MaxMin} + \gamma_B B_{MaxMin} + \varepsilon_{it}$$

	<i>Ask</i>				<i>Bid</i>			
	<i>A</i>		<i>B</i>		<i>A</i>		<i>B</i>	
α	1.096	***	0.881	**	-0.340	***	-0.431	*
γ_1	-0.048		-0.109		0.030	**	0.074	**
γ_2	0.289	***	-0.028		-0.226	***	-0.090	
γ_3	-0.180	***	-0.077		0.078	***	0.061	*
γ_A	0.525	***	-		-0.579	***	-	
γ_B	-		0.527	***	-		-0.639	***